Linguistic Model for Engine Power Loss

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***Abstract*—Army ground vehicles often operate in extremely severe environmental and battlefield conditions. Condition Based Maintenance (CBM) allows maintenance to be performed based on evidence of need provided by reliability modeling and/or other enabling technologies, thus reducing maintenance costs and increasing vehicle availability. A Takagi-Sugeno fuzzy model is developed to diagnose the loss of engine power of light trucks. Baseline data are acquired through engine performance measurements. The Adaptive Neuro-Fuzzy (ANFIS) training method is used to extract the fuzzy rules. To improve the quality of the model a combination of the least-square error and the backpropagation gradient descent methods is implemented to minimize the errors.**

Keywords- Condition Based Maintenance, fuzzy model, engine power loss, intelligent diagnostics

I. INTRODUCTION

In a theatre, the U.S. Army ground vehicles operate in extremely severe environmental and battlefield conditions. There are challenges for the reliability of the military ground vehicle fleet which need to be addressed. The Army intends to use computer based modeling and simulation to address these challenges. Reliability and safety computer simulations provide state-of-the-art tools to predict the reliability and safety of fielded trucks in off-design scenarios and physics-based prognostics criteria needed for condition-based maintenance (CBM) systems. CBM allows maintenance performed on evidence of need provided by the enabling reliability modeling, thus increases vehicle availability. A self-powered, cost-efficient, integrated intelligent system of sensors and microcontrollers for vehicle health monitoring is desired.

A significant segment of the Army's Light Tactical Vehicle Fleet is not equipped with any digital electronics that could directly contribute to CBM. In this paper, recent research results are described that are part of a larger effort to develop an Intelligent Vehicle Health Management System (IVHMS) for light trucks. In particular, this paper is focused on the system architecture for monitoring the power loss of the engine and the development of a fuzzy logic model for diagnostics. A commercial light truck has been chosen as an experimental vehicle platform.

The rest of the paper is organized as follows: in Section 2, a partial architecture and the associated functions of the IVHMS are presented. In Section 3, the engine failure modes considered for power loss diagnostics are summarized. In Section 4, experimental models for engine power loss are introduced. In Section 5, the fuzzy model and the creation of the fuzzy rules are described. In Section 6, the approach to optimize the membership functions is briefly explained. In Section 7, simulation results are presented. Conclusions are given in Section 8.

II. ENGINE MONITORING ARCHITECTURE

The functional block diagram of the engine monitoring section of the IVHMS is depicted in Fig. 1.

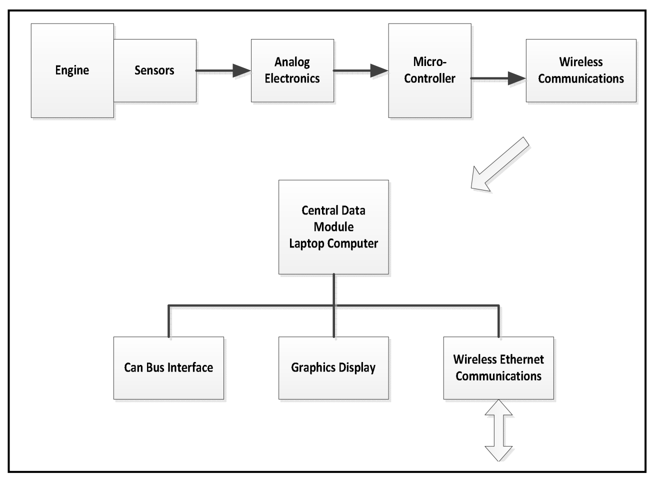

Figure 1. Engine monitoring system block diagram

All the electronic parts considered are off-the-shelf devices to leverage existing technologies and reduce cost. The microcontroller interfaced to the sensors provides for primary data manipulation/filtering and local data storage. Time stamps are attached to the sensory data collected at given intervals. In addition, the microcontroller firmware provides for off-loading the collected data via short-range wireless communications to a central data storage module located in a

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14. ABSTRACT
Army ground vehicles often operate in extremely severe environmental and battlefield conditions. Condition Based Maintenance (CBM) allows maintenance to be performed based on evidence of need provided by reliability modeling and/or other enabling technologies, thus reducing maintenance costs and increasing vehicle availability. A Takagi-Sugeno fuzzy model is developed to diagnose the loss of engine power of light trucks. Baseline data are acquired through engine performance measurements. The Adaptive Neuro-Fuzzy (ANFIS) training method is used to extract the fuzzy rules. To improve the quality of the model a combination of the least-square error and the backpropagation gradient descent methods is implemented to minimize the errors.

15. SUBJECT TERMS
Condition Based Maintenance, fuzzy model, engine power loss, intelligent diagnostics

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safe place on the vehicle. The sensor modules communicate with each other and with the central data module via a wireless interface that is compliant with the IEEE 802.15 protocol. The wireless personal area network is implemented using the ZigBee protocol.

The central data module integrates all data collected from the intelligent sensors attached to the various vehicle systems. A rugged laptop computer is used as the central data module. On demand, the central data module can upload its data along with the vehicle ID Number via another, secure short range wireless communications link, or via a wired Ethernet port to a mobile device (e.g., another laptop computer authorized for CBM). In addition, a CAN Bus interface is also available for vehicles that are equipped with a CAN Bus-based sensor system in order to collect that data as well.

The central data module performs basic monitoring functions based upon the sensed data and preset boundary values. If the sensed data reveals a critical situation in the status of the vehicle then alarm signals will be generated in real-time on the laptop computer's screen. In addition, the coordinator module has sufficient nonvolatile memory to store the sensory data on the vehicle over a long mission route.

The diagnosis and prognosis of the vehicle's health will be based upon both the data uploaded from the vehicle's central data module and a large, off-vehicle database containing failure mode data on the same vehicle and other vehicles of the same class of vehicles. The diagnosis part attempts to assess the status of failing or failed components of vehicle systems by the method of triangulating sensor information on the component as well as using measurement records of healthy and failed components. An intelligent diagnostic system is being developed using both analytical methods and fuzzy logic. A limited, rudimentary version of the diagnostics system is displayed on the screen of the vehicle's central data module laptop computer.

The prognostics feature will also be based upon actual vehicle data and a recorded vehicle failure data archive. Using fuzzy logic an intelligent system will be developed to infer qualitative predictions on the mission reliability of the vehicle to some time periods into the future.

III. ENGINE FAILURE MODES FOR DIAGNOSTICS

Fuzzy models have been used for monitoring and diagnosing faults in various internal combustion (IC) engine subsystems. In [1], wear of a single-cylinder diesel engine (as quantified by an increase in the clearance between the piston-cylinder interface) was successfully diagnosed using engine block vibration data and fuzzy logic (fuzzy nearness and fuzzy cluster) methods. Fuzzy model-based diagnostics have also been developed for the cooling system of a diesel engine, integrating a priori, 'expert' knowledge, sensor data, and the adaptive network-based fuzzy interference system (ANFIS). The model yielded successful fault diagnosis for 73 to 97.7 percent of the test data [2]. Failure detection and identification algorithms integrating fuzzy logic control and fuzzy based estimators have also been proposed and successfully demonstrated to isolate sensor faults (e.g., faults with mass air flow sensor) in internal combustion (IC) engines [3].

With internal combustion engines, problems with any of the major subsystems (i.e., fuel system malfunction, lack of compression, increased friction losses, increased heat losses and air induction) can manifest as a gradual or sudden loss in engine power. In order to diagnose the malfunctioning of a particular system, it is first necessary to understand what constitutes normal operation. Direct, in-situ measurements of representative engine parameters have been used to identify potential problems with engine operation.

The following parameters have been selected for measurement: engine output torque, throttle position, crankshaft rotational speed, exhaust gas temperature (EGT), pressure drop across the intake air filter and intake air temperature.

Sensor selection was based on the criteria of robustness, commercial availability and price. In order to avoid unnecessary complexity, built-in engine sensors are used whenever possible (e.g. throttle position and crankshaft sensors). Redundancy is built into the EGT measurement (i.e. ten sensors instead of eight) to investigate the possibility of reducing the total number of EGT sensors in the future. The type and quantity of sensors selected is shown in Table I.

TABLE I. Engine Diagnostic Sensors

Quantity measured	Sensor quantity
Throttle position	1
Output torque	1
Crankshaft speed	1
Pressure drop	1
Exhaust gas temperature	8 + 2 redundant sensors
Intake air temperature	1

In this paper, however, only one aspect of many possible engine power loss scenarios is considered and the full engine diagnostic matrix is not given. We focus on just one failure mode: the one that manifests itself as lower than normal exhaust gas temperatures (EGTs). By comparing the actual engine power with the nominal one the system may detect a power loss. The throttle position sensor (TPS) monitors the driver's input. The output torque and rotational speed are measured to calculate the engine output power. EGTs are recorded simultaneously to identify whether any significant change in the engine's output power is a cylinder-specific problem or a global problem. Based on the experimental result there is an expected value of throttle position for each load-speed measurement. In the normal case (no power loss) the measured value of the throttle position will be equal to the expected value of the throttle position, otherwise the difference between the expected value of the throttle position and the measured one gives indication of the power loss of the engine.

Laboratory tests have been conducted using a four-stroke, eight-cylinder, reciprocating diesel engine (identical to the engine that is mounted on the light truck) to benchmark performance (e.g., output power) and monitor EGTs as a function of speed and load. The stand alone engine is coupled

to a water-brake dynamometer and instrumented to acquire benchmark data under controlled conditions. This baseline provides a comparative basis with which to validate the diagnostic matrix. Experimental data obtained from the stand alone engine were used to devise the analytical correlations between the various measured parameters and engine power.

IV. Experimental Models For Engine Diagnostics

The relationship between the throttle position (TP) and the output power has been identified as an approximately linear relationship as shown in Fig. 2.

From the baseline data, the relationship between the throttle position and the EGT of the left exhaust collector and the right exhaust collector, respectively, are approximately linear as shown in Fig. 3 and Fig. 4, respectively.

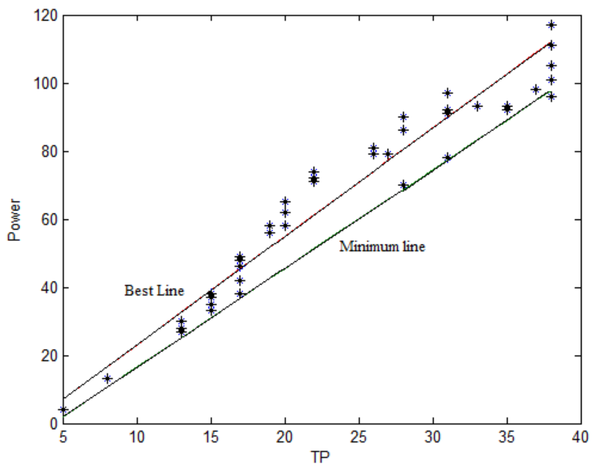

Figure 2. Throttle Position versus Power

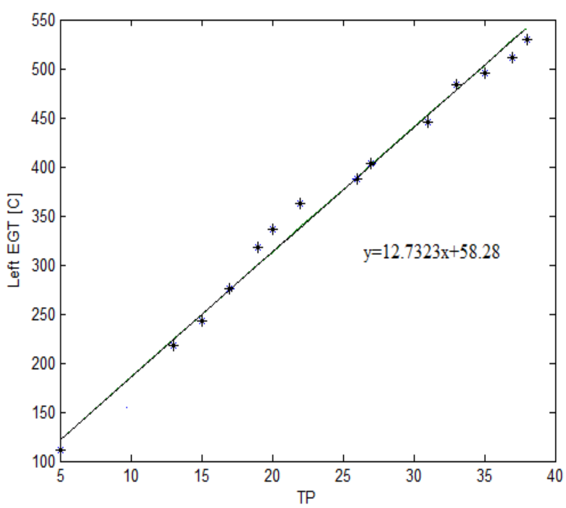

Figure 3. Throttle Position versus Left Collector EGT

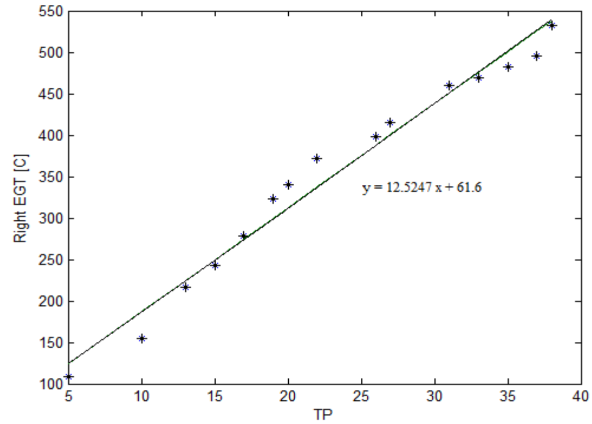

Figure 4. Throttle Position versus Right Collector EGT

V. Fuzzy Model For Engine Diagnostics

A Takego-Sugeno type [6] fuzzy logic model has been developed for the diagnosis of power losses in the vehicle, based on the torque, crankshaft rotational speed and throttle position (TP) measurements, as depicted in Fig. 5. The internal architecture of the model is shown in Fig. 6. The model has five inputs, three of them (i.e., speed, torque and TP) are fuzzy inputs to the ANFIS system and the other inputs (left collector EGT and right collector EGT) are used to determine the respective power loss causes. The model's outputs are the overall power loss, power loss due to the left EGT and power loss due to the right EGT, respectively.

Crankshaft speed and torque are used to calculate the output power of the vehicle, while TP represents the driver's power demand from the vehicle. On the grounds of the lab experiments, there is an expected value of TP for each torque-speed combination for normal cases (no power losses). Based on these results, an Adaptive Neural Fuzzy Inference System (ANFIS) was developed using MATLAB. The inputs of the ANFIS system are as follows: throttle position, speed and torque, while the output is the power loss in the vehicle. The fuzzy input membership functions are shown in Figs.7(a) to 7(c). The critical parameters of the membership functions and the fuzzy rules are determined by using the hybrid learning technique ANFIS. The ANFIS structure is given in Fig.8.

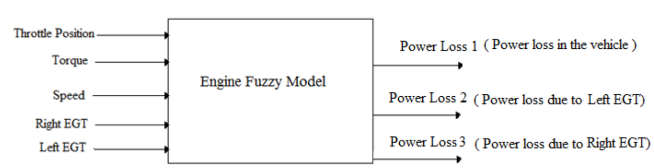

Figure 5. Fuzzy model for engine power loss

The relations between the TP and the EGTs are almost linear and can be described by the baseline equations. On the grounds of the TP measurements the expected value of EGTs can be calculated. Then the expected values are compared with

the measured ones to determine whether or not the power losses are due to malfunctioning engine cylinders.

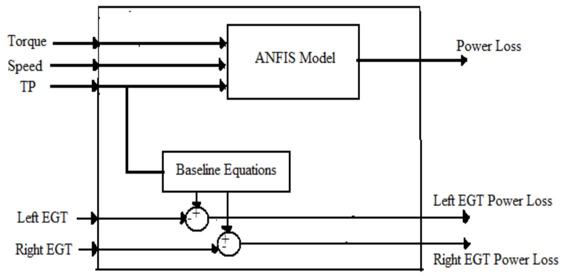

Figure 6. Internal architecture of the fuzzy model

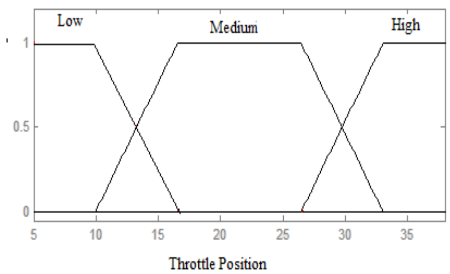

Figure 7(a). Membership functions for TP

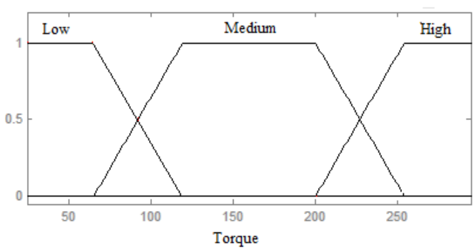

Figure 7(b). Membership functions for Torque

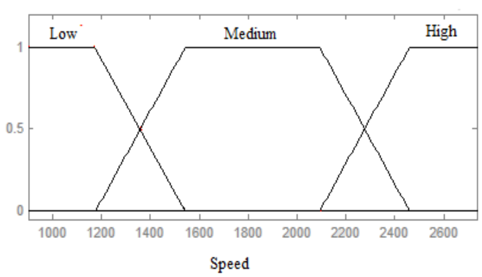

Figure 7(c). Membership functions for Camshaft Speed

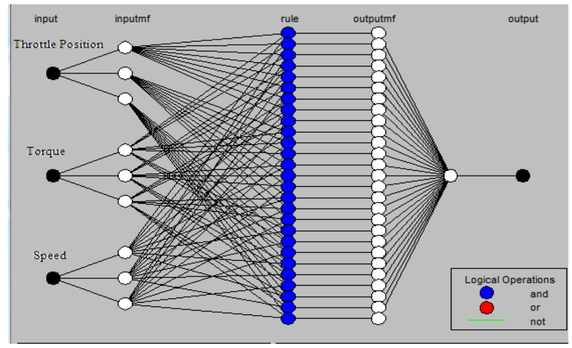

Figure 8. ANFIS model structure

VI. THE ANFIS SYSTEM

The input fuzzy membership functions are shown in Figs. 7(a) to 7(c). Each membership function is defined by a set of parameters. Those critical parameters can be potentially determined by using experts' domain knowledge. However, in a nonlinear system in which not all possible causes to engine power loss are considered and measured, merely relying on expert knowledge may not be sufficient to develop a reliable model. In order to improve the performance of the fuzzy system a learning algorithm can be used to extract the critical parameters from the set of input data. A first order Takagi-Sugeno fuzzy system along with a hybrid learning algorithm is used to define the membership function parameters [4, 5].

In the Takagi-Sugeno fuzzy model [6], the consequent of the IF-THEN rules is the linear combination of the inputs:

R: If x_1 is A_1, ..., x_k is A_k then $y = g(x_1,...,x_k)$

and g is a linear function such that

$$g = p_0 + p_1x_1 + ,..., + p_kx_k \qquad (1)$$

where $A_1,\ldots, A_k$ are fuzzy sets, $x_1,\ldots, x_k$ are fuzzy inputs and output y is obtained as a crisp value.

The hybrid learning algorithm is a combination of the back propagation steepest descent and the least square methods to obtain the critical parameters of the membership functions. In this system those parameters will be recalculated as soon as more measured input data become available to improve the quality of the model. One of the advantages of this system is that it can be initialized by a reasonable set of fuzzy rules based upon expert knowledge and some measured data, even though the expert knowledge may not cover for extreme cases. Another advantage is that while the engine's performance will change over several years of use, the ANFIS model will adapt to it by using updated training data.

VII. SIMULATION RESULTS

The combined model for engine power loss (the ANFIS fuzzy model and the base line equations) has been created by collecting data from stand-alone engine tests. In order to investigate the performance of the fuzzy model, the output power of the engine has been measured and has also been

estimated by using the ANFIS model as well as the left collector EGT and right collector EGT base line equations, respectively, as it is shown in Table II. The first column in Table II represents the measured output power. Data in the second column are of output power values calculated by using the ANFIS model. Column 3 shows output power values calculated by using the left collector EGT base line equation, while Column 4 exhibits the output power calculated by using the right collector EGT baseline equation. Columns 5, 6 and 7 exhibit the difference between the measured and the calculated output power values using ANFIS, the left and right EGTs, respectively. As it is shown in Table II, the ANFIS model is more accurate in estimating the engine power with respect to the baseline equations. On these grounds, ANFIS is deemed more accurate for estimating the engine power losses except for the last test. In that case it has produced a higher relative error than that of the baseline equations. This discrepancy is attributed to the relative lack of input data that cover this range.

The graphs in Fig.9 show that the error introduced by the fuzzy model is lower than the typical test measurement uncertainty. The level of imprecision for the measurements was very high for the last tests and this is the reason for having high value of the relative error of ANFIS compared with the baseline equations.

TABLE II. Power loss calculations using the ANFIS model and the EGTs

Base Power calculated from measurement [HP]	Base power from ANFIS [HP]	Base power from Left EGT [HP]	Base power from Right EGT` [HP]	Error of ANFIS model	Error of left EGT	Error of right EGT
4.0000	3.9998	4.7331	3.0686	0.0002	0.7331	0.9314
11.0000	10.998	15.247	14.495z0	0.0025	4.2466	3.4950
28.3000	27.7039	30.8946	29.6474	0.5961	2.5946	1.3474
35.7000	35.8146	37.0071	36.3542	0.1146	1.3071	0.6542
44.6000	45.1016	45.0756	45.0482	0.5016	0.4756	0.4482
57.0000	57.2718	55.3446	56.2262	0.2718	1.6554	0.7738
62.5000	63.8176	59.7456	60.4490	1.3176	2.7544	2.0510
72.3000	72.3217	66.3471	68.3978	0.0217	5.9529	3.9022
80.0000	80.4093	72.2151	74.8562	0.4093	7.7849	5.1438
79.0000	79.0002	76.1271	79.0790	0.0002	2.8729	0.0790
89.5000	88.8599	86.6406	90.2570	0.6401	2.8594	0.7570
93.0000	93.0000	95.9316	92.4926	0.0000	2.9316	0.5074
92.5000	92.5159	98.6211	95.7218	0.0159	6.1211	3.2218
98.0000	97.9090	102.5331	99.1994	0.0910	4.5331	1.1994
106.0000	108.8536	107.1786	108.1418	2.8536	1.1786	2.1418

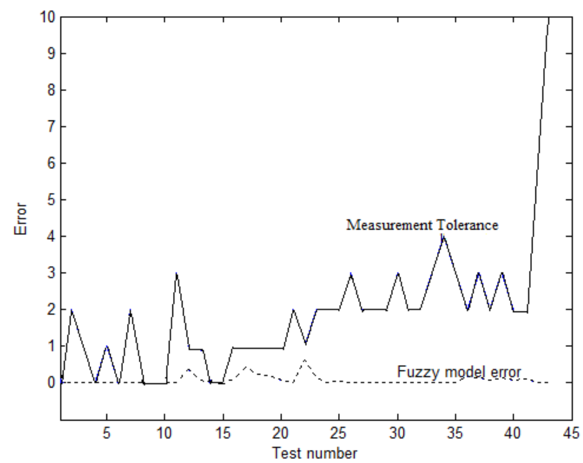

Figure 9. Fuzzy model error and measurement error in tests

In preparation to extend the engine model to cover for power losses due to air intake obstruction, and to further verify the performance of the ANFIS model additional tests have been conducted. In a test with 50% intake obstruction, the output power was calculated by multiplying the measured value of the torque with the measured value of the crankshaft speed. The ANFIS system was used to determine the expected (base) power from the measured values of the speed, torque and TP. The results are depicted in Fig.10. For this test, the expected output power value must not be the same as the measured one because of the 50% intake obstruction. As it is shown in Fig. 10, the expected engine power that is calculated using the ANFIS model runs higher than the measured one due to the power losses induced by the partially blocked air intake.

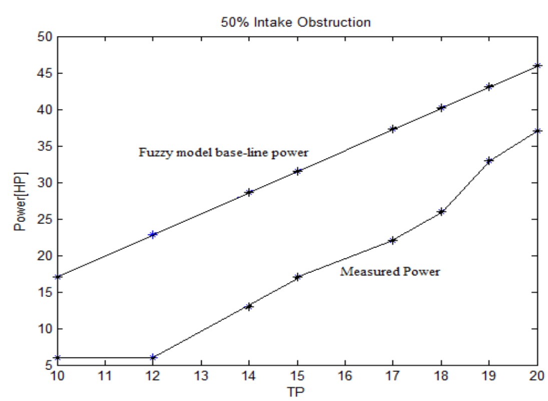

Figure 10. Expected power (by ANFIS) versus measured power with 50% intake obstruction

The graphs in Fig.11 and Fig.12 show the expected output power of the engine for the 50% intake obstruction test as calculated using the measured values of TP, left collector EGT and right collector EGT, respectively. Again, as it is depicted in Fig. 11 and Fig.12 the expected output power value is higher than the measured one due to blockage of intake air filter.

The relative differences between the measured engine power and the expected power for the 50% intake obstruction test using ANFIS, left EGT and right EGT baseline equations, respectively, are shown in Fig.13. As it is indicated in Fig.13, ANFIS has the highest difference compared to the left and right collector EGT base line equations. Hence, it is likely that an extended ANFIS model with an added differential intake pressure sensor input data will deliver a better diagnosis on the engine power loss problem.

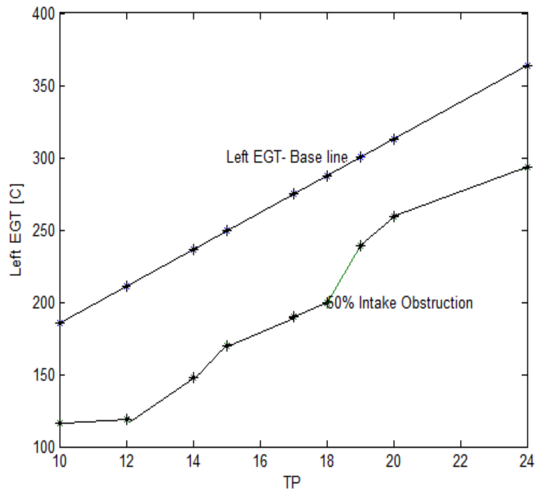

Figure 11. Expected power (by left EGT baseline equation) versus measured power with 50% intake obstruction

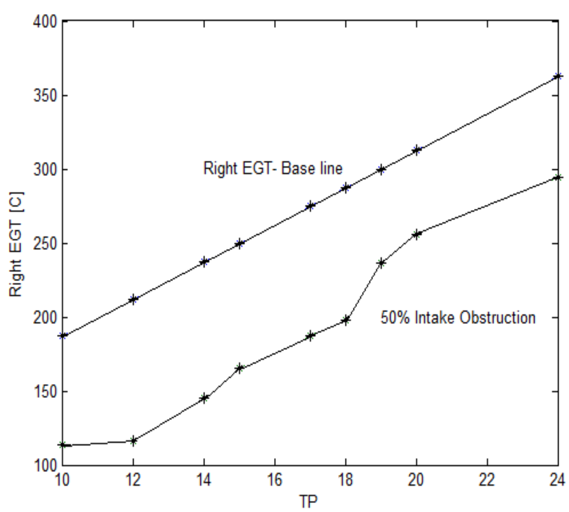

Figure 12. Expected power (by right EGT baseline equation) versus measured power with 50% intake obstruction

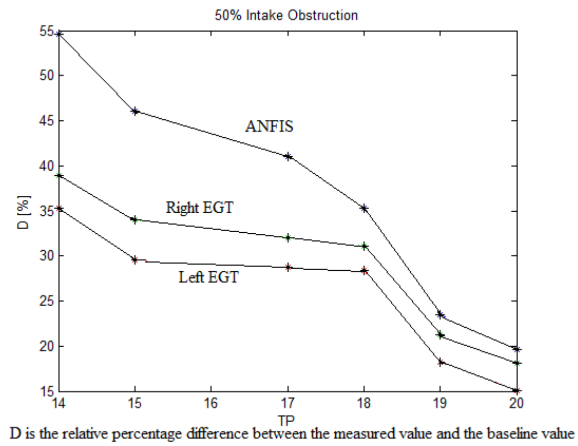

Figure 13. Relative differences between the expected engine output power and the measured output power with 50% intake obstruction using ANFIS, left EGT and right EGT baseline equations

VIII. Conclusions And Future Work

The basic architecture of an engine health monitoring system for light tactical vehicles is presented and its objectives are outlined. A fuzzy model is introduced to deal with the problem of diagnosing engine power loss. Stand-alone engine experimental data are collected to generate an initial set of training data for the fuzzy model. The ANFIS model is used to define the critical parameters of the membership functions and fuzzy rules. The simulation results indicate that the ANFIS model and EGT measurements can be used to diagnose the power loss of the vehicle.

Future work may focus on modifying the fuzzy model in two ways; one is to replace the EGT baseline equations by another ANFIS system (since it can deliver better results) and the other is to expand the diagnosis to the other causes for power loss of the engine.

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REFERENCES

[1] Zhang, Y., Zhang, Z. P., Zhou, Y.C., Research on the fuzzy and dynamic monitoring of the diesel engine operating conditions. Proc Instn Mech Engrs, vol 212: D5, pp.421-426,1998.

[2] Twiddle, J.A., Jones, N.B., Fuzzy model-based condition monitoring and fault diagnosis of a diesel engine cooling system. Proc Instn Mech Engrs, vol 212, vol. 216:3, pp/215-224, 2002.

[3] Yasin, S.Y., Hashemipour, M., Ganesan, S., Sharma, R.P. Fuzzy logic control based failure detection and identification (FDI) module for internal combustion (IC) engines. SAE Transactions, vol 115:7, pp.675-684, 2007

[4] Jang, J.-S.R., ANFIS: adaptive-network-based fuzzy inference system, *Systems, Man and Cybernetics, IEEE Transactions on* , vol.23, no.3, pp.665-685, May/Jun 1993.

[5] Rizzi, A.; Mascioli, F.M.F.; Martinelli, G , Automatic training of ANFIS networks, Fuzzy Systems Conference Proceedings, 1999 FUZZ-IEEE International Conference, vol.3, pp.1655-1660, 22-25 Aug. 1999.

[6] T. Takagi and M. Sugeno, Fuzzy identification of systems and its application in modeling and control, *IEEE Trans.on Systems, Man and Cybernetics,* vol. 15, 1985, pp. 116-132.